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Development of an Early Warning Multi-criteria Fire Detection System: Analysis of Transient Fire Signatures Using a Probabilistic Neural Network

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This report describes the progress made in developing an early warning, multi-criteria, fire detection system for the Office of Naval Research (ONR) program on Damage Control: Automation for Reduced Manning (DC-ARM). In this work, the analysis of transient fire signatures is studied using a probabilistic neural network (PNN). Experiments are described to study the effects of various PNN training parameters and to determine the optimal sensor suite combination, which enables both early fire detection and high nuisance source rejection. Comparisons are made between the candidate sensor arrays, commercial fire detection systems, and sensor arrays proposed in previous reports. Recommendations and directions for future research are also given.

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INTRODUCTION

Early detection of fires is a critical component of the Office of Naval Research's Damage Control: Automation for Reduction Manning (DC-ARM) program. The research described in this report is a continuation of a collaboration between the Naval Research Laboratory (NRL) and Hughes Associates to develop and evaluate an early warning, multi-criteria fire detection system for use in DC-ARM [1,2]. In this program, Hughes Associates collected a large database containing the signatures from real and nuisance alarm sources for several different types of sensors. Our approach to early fire detection is based on the premise that a combination of sensor technologies coupled with pattern recognition methods could provide for faster, more accurate fire detection than any single sensor technology that measures a physical quantity (e.g., particles or heat) or a fire decomposition vapor (e.g., CO_2, O_2). Previous research in the analysis of these fire signatures produced several combinations of sensors that could provide increased detection sensitivity, decreased detection time and improved nuisance source false alarm rejection [1,2]. Those experiments assumed that a baseline sensor reading could be obtained for the smoke detectors.

The work described in this report takes a slightly different approach. Here we assume that it will not be possible to determine an appropriate baseline level and all analyses are performed on the raw sensor outputs. This makes the fire detection problem more difficult since the day-to-day variation in sensor readings is not removed. Using this raw data, we investigated several data analysis issues critical to developing an early warning, multi-criteria fire detection system including:

1. the importance of the sensor rate of change (i.e., slope);
2. the best sensor combinations;
3. earliest possible fire detection times; and
4. the optimal procedure for training the probabilistic neural network.

EXPERIMENTAL

In this study, the large fire signature database described in reference 2 was used. This database consists of data from twenty different sensors for 88 fire events and 38 nuisance sources. Table 1 provides a list of the twenty sensors used in this study. Because the MIC sensor produces three different sensor readings, a total of 22 sensor outputs were studied. During preliminary investigations it was discovered that the ODM sensor stopped working during the middle of the four experiments (DCAS012, DCAS015, DCAS018, and DCAS019). During DCAS054 and DCAS057, the photoelectric smoke sensor was not operation. It was felt that these abnormal sensor readings might bias the neural network, so these six experiments were removed from

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further analysis to avoid skewing the results. The resulting database contains 120 experiments (82 fires and 38 nuisance events). For fire classification analysis, we also consider the period in each experiment prior to ignition. During this background or baseline time period, the sensors were not purposely exposed to any fire or nuisance products. Any changes in the sensor readings during these time periods represent the day-to-day or experiment-to-experiment normal fluctuations in the sensor outputs.

Because this study involved the use of raw sensor data, any changes to the sensor electronics can also bias the results unless corrected. During the course of the 120 experiments in the database, Hughes Associates changed output circuitry (gain) for the ODM sensor to reduce noise in the output signal. This caused the sensor readings to vary greatly over the course of the experiments. However, the gain correction is a linear function and the sensor values can be scaled so that they appear to all have the same gain setting. Most experiments (DCAS031-DCAS145) were conducted with a 470 Ohm resistor, which produced sensor readings on the order of 0.16 Volts. Experiments DCAS009 through DCAS027 had an average baseline voltage of approximately 2.2 volts, while DCAS028, DCAS029 and DCAS030 had baseline voltages of nearly 5.0 volts. According to Hughes Associates, these experiments used 10,000 Ohm and 22,000 Ohm resistors. Using a simple linear correction factor, it was possible to make all ODM sensor values to appear as though the 470 Ohm setting was used. The scaled ODM data was used for all further experiments.

The two commercial fire detectors (SION and PHOT) were collected at 4 or 5 second intervals compared to once per second for the other 18 sensors. The sensor outputs for all 20 sensors were combined using the times that the SION and PHOT output values were collected. This combined data file was used for all subsequent experiments.

All calculations were done in MATLAB (version 5.2, Mathworks, Inc., Natick, MA) on a personal computer. Probabilistic neural network (PNN) training and cross-validation were performed using the *MAGICAL* program written by the authors. Correlation maps were created using routines from the PLS_Toolbox (version 2.1, Eigenvector Technologies, Inc., Manson, WA).

Table 1. Sensor Instrumentation for Multi-Criteria Fire Detection Tests

Number	Code	Name	Sensor Range
1	HCN	Hydrogen Cyanide	0-25 ppm
2	CO_2	Carbon Dioxide	0-5000 ppm
3	O_2	Oxygen	0-25%
4	CO	Carbon Monoxide	0-50 ppm
5	CO-2	Carbon Monoxide	0-4000 ppm
6	H_2	Hydrogen	0-200 ppm
7	HCl	Hydrogen Chloride	0-10 ppm
8	H_2S	Hydrogen Sulfide	0-5 ppm
9	SO_2	Sulfur Dioxide	0-10 ppm
10	NO	Nitric Oxide	0-20 ppm
11	NO_2	Nitrogen Dioxide	0-5 ppm
12	Ethy	Ethylene (hydrocarbons)	0-50 ppm
13	TC	Temperature	-200-1250 °C
14	OMEG	Temperature	-20-75 °C
15	RH	Relative Humidity	3-95%
16	MICX	Measuring Ionization Chamber	
17	MIXY	Measuring Ionization Chamber	
18	MICZ	Measuring Ionization Chamber	
19	ODM	Optical Density Meter	
20	RION	Commercial Residential Ion	
21	SION	Commercial Simplex Ion	1.6-10% Obs/m
22	PHOT	Commercial Photoelectric	0-19% Obs/m

RESULTS AND DISCUSSION

Probabilistic Neural Networks

Pattern recognition methods provide an automated means of distinguishing between data classes. For multi-criteria early warning fire detection, pattern recognition methods treat the pre-processed sensor data as a vector ("pattern") in multidimensional space. Recognition of a fire is based on the clustering of the patterns in the multidimensional space. Successful identification is dependent upon the sensor signals being able to numerically encode the fire and nuisance source signatures and that there are reproducible differences between the signatures of real fires and non-real fire events. In supervised pattern recognition, prior information about class membership is known for each pattern (e.g., fire or non-fire). The training set patterns are obtained by exposing the sensors to a wide variety of conditions (e.g., different types of fires). A supervised pattern recognition algorithm "learns" classification rules from the training set in order to predict the classification of sensor readings occurring from future events.

Because the clustering of the fire and non-fire events lends itself to a multi-modal class distribution, a nonlinear method of pattern recognition is required. One type of supervised pattern recognition method that we have used successfully for sensor array

pattern recognition is the probabilistic neural network (PNN) [3,4]. The PNN was used in our previous reports on fire detection [1,2] and will only be discussed briefly here.

The PNN is modeled after the Parzen classifier, which implements a multivariate probability estimator using a probability density function (PDF). A PDF for each category (fires and non-fires) is generated by a series of Gaussian kernel functions centered at the pattern vectors in the training set. The only parameter that is optimized during PNN training is the width of the Gaussian kernels. In this work, an NRL developed algorithm for fast kernel width optimization was used [4]. Three layers of neurons or mathematical processing step (hidden, summation, and output) make up the composition of the PNN. The hidden layer stores the patterns in the training set and implements the Gaussian kernel function. The hidden layer has as many neurons as there are patterns in the training set. The summation layer contains as many neurons as there are data classes (two in this work) and collects the common outputs from the hidden layer neurons. The outputs from the summation layer are then sent to the output layer where the probability of being a real fire or a non-fire is computed. The pattern is placed in the category with the highest probability.

The PNN algorithm was implemented using MAGICAL (**MA**tlab **G**raphical **I**nterface for **C**lassification **AL**gorithms), which was written by the authors. Because the PNN uses all the patterns in the training set to classify new patterns, leave-one-out cross validation (CV) was used to obtain an unbiased estimate of prediction classification performance. CV involves many iterations of training and testing. For each iteration, the PNN is trained using all the patterns in the training subset except one, called the holdout pattern. The trained algorithm is then used to predict the classification of the holdout pattern. This process is repeated until each pattern has been left out once. The percentage of held out (or leave one out) patterns correctly identified is a good measure of how well the PNN will perform on new data. A better measure would be external validation using a prediction set, but the collection of additional fire data is expensive and time-consuming. CV offers a good compromise for the DC-ARM program.

Alarm and Sensor Response Time Studies

In order to determine the optimal method for training the PNN and to find the earliest possible times when fires could be correctly identified by a multi-criteria protocol several experiments were performed. In previous work, training sets for PNN fire detection were created at three different time periods ("slice in time"). These preliminary experiments were geared towards feasibility studies rather than optimization for real-time implementation so choosing training and prediction sets from a single point in time (i.e., time slice) was justifiable. Due to the dynamic nature of fires choosing when to select fire and nuisance patterns is difficult. Patterns taken from early in an event may appear much different than patterns obtained later in the experiment. In addition, there are many uncontrollable variables which effect the transient nature of the event, which makes choosing the optimal training patterns even more difficult. This aspect is much different than other sensor array projects for chemical detection. During the feasibility studies, it was determined that a large-scale optimization of the optimal times at which to train the PNN was not necessary. It was decided to use the alarm time of a standard commercial fire detector to determine when the PNN training pattern should be created. This decision made sense on several levels because it provided for a benchmark standard for comparison and several commercial smoke detectors were already part of

the sensor suite in the fire chamber experiments. In this work, the first sets of experiments will continue this logic; later experiments will expand on this approach to include additional times for creating training sets that are not based on a commercial fire detector. Additional experiments will then be conducted to incorporate patterns from multiple training sets.

During the data collection effort, the PHOTO commercial fire detector alarm time was noted for three different settings 11%, 1.63%, and 0.82% obscuration (Obs.)/m, representing a typical least sensitive setting, the UL Standard 268 minimum alarm level, and half the UL standard, respectively. The third setting corresponds to very sensitive smoke detector. For the remainder of the report these alarm times will be referred to as response time or PNN training time #1, #2 and #3, respectively. The terms, PNN training time and response time, will be used interchangeably throughout the report. There is a direct link or correlation between the two terms because a PNN trained at an earlier time period will generally result in a fire detection system that classifies events earlier (i.e., faster response) than a PNN trained using later time slices. In addition to the three times based on the commercial smoke detector, two methods based on all the sensor readings were used to obtain time periods for creating patterns for neural network training. These methods were based on following the fire signatures as a function of time until five or more sensors had deviated from baseline conditions. Baseline conditions were based on the mean and standard deviation sensor output for the first 15 data points (roughly 60 seconds) of each experiment. Ignition (fire or nuisance source initiation) for all experiments occurred sometime after the 60 second baseline period. The criteria for detection was when the sensor shift (current sensor output - mean baseline sensor output) for a certain number of sensors was larger than 5-10 times the standard deviation of the baseline sensor output. For sensor response time method #4, the number of sensors was set to 5 and the standard deviation criterion was 10. While for sensor response method #5, the number of sensors was 10 and the standard deviation was 5. In several experiments, these criteria were too stringent and were never met. For those cases, the criteria were relaxed by either reducing the number of sensors or the standard deviation. One consideration for interpreting the results from the PNNs trained at the different response times is that the algorithms trained using time slices taken early in an event will most likely result earlier fire detection, but will be more prone to false alarms since the sensor readings may not have deviated far from the baseline. This provides the rationale for training the PNN at increasingly earlier time slices so that we can determine when nuisance source and background rejection is no longer successful.

Table 2 contains the experiment name, experiment number, ignition time (source initiation) and the PNN training times (relative to the initiation of data collection) for the three commercial photoelectric detector (PHOT, sensor #22) settings and the two other sensor response methods. Alarm times for methods #1-3 can be found by subtracting the ignition times from the reported PNN training time. For real fire sources, the median difference between the most sensitive commercial fire detector setting (0.82% Obs/m) (sensor response method #3) and sensor response methods #4 and #5, were 89 seconds and 0 seconds, respectively. A multi-criteria fire detection system trained at the sensor response time #4 should detect fires the earliest among the 5 methods, but because only 5 sensors were significantly different from baseline reading, this method may be prone to false alarms. Sensor response method #5 is interesting because it produced response times that were faster than the most sensitive photoelectric detector setting, which is based on smoke and particle detection only, half the time and was

slower the other half. For fire scenarios that generate smoke or particles early, the photoelectric detector alarm starts before most of the other sensors had changed significantly from baseline (e.g. DCAS104, smoldering LSDSGU-14). Other types of fires, such as the heptane fires (e.g., DCAS024-026, DCAS041), produce larger amounts of fire products and cause several sensors to deviate from their baseline levels earlier in the event compared to smoldering fires.

Table 2. PNN Training Times for the Five Sensor Response Methods

Name	#	Ignition (sec)	Sensor Resp. #1 (sec) Photo 11%	Sensor Resp. #2 (sec) Photo 1.63%	Sensor Resp. #3 (sec) Photo 0.82%	Sensor Resp. #4 (sec)	Sensor Response #5 (sec)
DCAS009	1	70	449	449	449	113	125
DCAS010	2	60	440	163	163	109	113
DCAS011	3	62	335	235	176	121	155
DCAS013	4	90	340	227	227	143	168
DCAS014	5	65	332	105	105	110	126
DCAS016	6	60	1640	1145	822	633	948
DCAS017	7	60	2576	1259	655	554	1112
DCAS020	8	75	465	465	465	164	441
DCAS021	9	80	590	590	590	138	277
DCAS022	10	90	540	540	540	134	290
DCAS023	11	60	540	540	540	151	461
DCAS024	12	90	865	437	290	176	223
DCAS025	13	88	885	420	264	164	264
DCAS026	14	80	885	449	302	201	239
DCAS027	15	178	353	244	239	201	239
DCAS028	16	100	298	189	155	160	227
DCAS029	17	60	510	510	510	717	612
DCAS030	18	90	264	142	138	151	193
DCAS031	19	95	226	151	142	159	205
DCAS032	20	95	285	180	155	159	230
DCAS033	21	145	289	214	210	197	210
DCAS034	22	105	239	167	159	159	214
DCAS035	23	113	629	629	629	247	419
DCAS036	24	95	344	344	344	155	227
DCAS037	25	95	659	659	659	160	248
DCAS038	26	80	600	600	600	147	210
DCAS039	27	60	260	260	260	138	159
DCAS040	28	60	193	193	193	138	151
DCAS041	29	65	789	265	185	135	172
DCAS042	30	105	319	243	235	177	218
DCAS043	31	85	293	252	243	168	218
DCAS044	32	85	373	373	373	184	268
DCAS045	33	85	374	357	336	168	265
DCAS046	34	95	156	151	151	147	156

Name	#	Ignition (sec)	Photo 11% (sec)	Photo 1.63% (sec)	Photo 0.82% (sec)	Sensor Response #4 (sec)	Sensor Response #5 (sec)
DCAS047	35	95	168	147	147	151	159
DCAS048	36	60	3931	667	617	390	612
DCAS049	37	60	2639	528	512	356	684
DCAS050	38	90	4699	3831	3781	831	1251
DCAS053	39	60	763	210	138	117	147
DCAS055	40	60	2005	2005	2005	1581	2399
DCAS058	41	60	537	168	143	101	113
DCAS059	42	60	1280	1238	1230	659	1234
DCAS060	43	60	449	310	298	277	402
DCAS061	44	60	1259	1229	1020	931	1166
DCAS062	45	60	818	487	474	432	495
DCAS063	46	60	660	660	660	172	369
DCAS064	47	60	113	105	105	101	118
DCAS065	48	71	731	731	731	131	177
DCAS066	49	60	949	474	424	118	126
DCAS067	50	60	353	248	231	118	134
DCAS068	51	60	650	650	650	143	172
DCAS073	52	60	325	325	325	344	349
DCAS074	53	60	785	785	785	269	533
DCAS075	54	60	709	655	634	256	432
DCAS076	55	60	482	440	436	373	453
DCAS077	56	60	432	415	407	365	432
DCAS080	57	60	610	610	610	222	407
DCAS081	58	60	578	578	578	268	407
DCAS082	59	60	919	919	919	567	374
DCAS083	60	60	978	378	374	143	1066
DCAS084	61	60	986	982	596	533	1041
DCAS085	62	97	402	402	402	109	121
DCAS087	63	165	480	480	480	223	390
DCAS088	64	130	516	491	483	147	151
DCAS089	65	66	588	227	185	181	369
DCAS090	66	80	818	265	210	248	768
DCAS091	67	156	705	294	273	265	605
DCAS092	68	60	412	412	412	420	428
DCAS093	69	125	510	510	510	520	529
DCAS094	70	60	126	126	126	667	386
DCAS095	71	60	860	860	860	360	805
DCAS096	72	60	500	441	437	428	521
DCAS097	73	60	512	449	436	445	541
DCAS098	74	60	482	461	457	457	495
DCAS099	75	65	995	995	995	936	995
DCAS100	76	60	1049	1024	1020	973	1036
DCAS101	77	60	953	881	835	756	940
DCAS102	78	60	663	646	629	600	688
DCAS103	79	60	826	738	713	633	1074

Name	#	Ignition (sec)	Photo 11% (sec)	Photo 1.63% (sec)	Photo 0.82% (sec)	Sensor Response #4 (sec)	Sensor Response #5 (sec)
DCAS104	80	60	1116	915	873	1037	1137
DCAS105	81	67	449	357	344	294	487
DCAS106	82	103	885	692	667	630	1116
DCAS107	83	103	1066	772	713	630	1217
DCAS109	84	60	688	676	667	554	650
DCAS110	85	60	537	474	465	398	524
DCAS111	86	60	671	612	595	407	625
DCAS112	87	60	692	579	558	449	642
DCAS113	88	60	1062	734	684	457	642
DCAS114	89	60	932	789	630	512	902
DCAS115	90	73	579	491	474	382	503
DCAS116	91	68	248	248	248	273	202
DCAS117	92	76	277	277	277	251	352
DCAS118	93	68	868	868	868	155	306
DCAS119	94	71	416	416	328	160	223
DCAS120	95	70	260	260	260	160	277
DCAS121	96	81	378	269	265	177	256
DCAS122	97	69	428	268	231	138	155
DCAS123	98	73	369	348	315	160	269
DCAS124	99	68	189	164	152	139	189
DCAS125	100	66	281	222	210	151	214
DCAS126	101	110	654	243	167	167	268
DCAS127	102	68	286	286	286	156	248
DCAS128	103	65	344	331	306	151	264
DCAS129	104	62	298	298	223	156	231
DCAS130	105	65	713	650	357	164	613
DCAS131	106	63	491	185	168	168	466
DCAS132	107	65	634	370	181	139	370
DCAS133	108	60	860	860	860	894	894
DCAS134	109	60	660	660	210	311	462
DCAS135	110	60	660	660	300	549	713
DCAS136	111	60	660	660	240	701	701
DCAS137	112	60	1260	1260	1260	1284	1422
DCAS138	113	60	2010	2010	2010	1565	1107
DCAS139	114	60	960	960	960	109	164
DCAS140	115	60	960	720	420	118	139
DCAS141	116	60	960	960	600	105	151
DCAS142	117	60	852	231	231	143	256
DCAS143	118	60	516	214	159	143	302
DCAS144	119	66	835	307	227	139	378
DCAS145	120	60	788	176	126	117	155

Sensor Rate of Change

In addition to using different times to train the PNN, we were interested in determining whether the sensor rate of change (i.e., slope) was important for discriminating between fire events, nuisance sources and background conditions. To investigate this issue, PNN training and prediction patterns were created using three different methods at each of the five PNN training times shown in Table 2. The software for creating training and prediction sets (*create_fire_train* and *create_fire_pred*) was written so that 8 different possible window sizes and combinations of slopes and magnitudes could be studied. However, due the large number of experiments needed to study the other issues, only 3 of these window selection methods was actually used. Table 3 lists an overview of the three methods used in this work. The first method (A) considered only the average sensor value (magnitude) over a five point window. Because data points occur roughly 4 to 5 seconds apart, the pattern magnitude is computed across a 20-25 second time window. Each initial pattern contained 22 variables corresponding to each of the 22 sensors. Methods B and C augmented these patterns with slope information. A window size of ten was used for method 4, while method 8 used a window size of 10 for computing the magnitude and 25 for computing the slope. These window sizes (5, 10 and 25) correspond to approximately 20, 40 and 100 seconds, respectively. The selection of these window sizes was based on the observation that the transient response of a fire is often on the order of minutes and that slope information computed from a small window would be highly susceptible to noise or spurious sensor changes. A larger time window (10 or 25 points) might be better for slope but poor for magnitude. When slope information is included in the pattern, the pattern vector used for PNN analysis contains 44 variables (22 magnitude + 22 slopes). The 22 slope variables are simply concatenated to the end of the pattern vector of magnitudes and in the following discussions are referred to as variables 23-44. Thus, variable 34 is the slope of the hydrocarbon sensor (#12). Sensor slope variables will be denoted in the text using the symbol Δ (delta) to differentiate them from sensor magnitudes.

Table 3. Summary of Window Sizes and Methods Used to Create Patterns for PNN Analysis

Descriptor	Method A	Method B	Method C
Magnitude	Average sensor output over 20-25 s	Average sensor output over 40-50 s	Average sensor output over 40-50 s
Rate of Change	N/A	Slope over 40-50 s	Slope over 100-120 s

Feature Selection

The final issue under study concerned feature or variable selection for the PNN. In these experiments, the variables are the sensor magnitudes and slopes. Feature selection serves two purposes: (1) to help discern the importance of slope information and (2) to aid in selecting the optimal set of sensors for early fire detection. Three feature selection algorithms were studied in this work. The first method, *calibsel*, was studied in the previous work and is based upon simple linear regression [1,2]. Variables are selected based on their ability to provide a linear separating surface between fires and non-fires (nuisance and backgrounds). The second method, *expert*, is based upon

earlier studies that suggested that certain combinations of gas sensors and smoke/particle detectors would perform favorably. The third method, forward selection PNNCV, is based on the forward selection protocol with the sum of squared error (SSE) from PNNCV as the criterion. The SSE is computed using equation 1,

$$error = \sum_{i=1}^{n} \left[\left((1 - p_{i,k})^2 + \sum_{k \neq j} (p_{i,j})^2 \right) w_k \right] \tag{1}$$

where $p_{i,k}$ is the predicted probability of being the correct class, $p_{i,j}$ is the predicted probability of all the other classes, w_k is the weight factor for each class, and n is the number of patterns in the training set. In this work the weight factor was set to one so that both fires and nuisances would be weighted equally. The SSE estimates how well the PNN will perform in prediction. Smaller SSE indicates a better trained PNN. The forward selection PNNCV algorithm was incorporated into a larger program called *varselpr* for performing variable selection for pattern recognition. For simplicity, the forward selection PNNCV routine will be termed *FSPNNCV* for the remainder of the report. Starting with a single variable, *FSPNNCV* finds the variable that produces the lowest SSE. Then, using this sensor, the algorithm finds the best two sensor combination and so on until the desired number of variables is chosen. In this work, the maximum number of sensors chosen by the approach was limited to five. In a few cases both the slope and the magnitude for a sensor were selected resulting in a total of 6 variables. Some additional experiments were conducted to determine the improvement that might occur when increasing the number of sensors to 10.

Experimental Protocol

In order to study sensor response times (time slices for training the PNN), PNN training protocol, and feature selection, an experimental design study was configured. As discussed above five different PNN training time slices were used. In these initial experiments only the three commercial photoelectric alarm times (denoted 1, 2, and 3, see Table 2) were studied. Three window sizes were studied and listed as A (5 point window, magnitude only), B (10 point window, magnitude and slope), and C (10 point magnitude and 25 point slope) as described in Table 3. Three feature/variable selection methods were studied and denoted as *expert*, *calibsel*, and *FSPNNCV* as described previously.

Each experiment consisted of six steps.

1. Using a MATLAB script called "*create_fire_train*", the magnitude (and slope if desired) for each sensor was computed using the desired window size (A, B, or C) at the desired response time (Table 2). This program produced the five training sets for fire detection.

2. A MATLAB script called "*create_fire_pred*" was then run to compute magnitudes (and slopes if necessary) from sensor data taken from the entire experiment (i.e., at every time step). Thus, the prediction set has pattern vectors from baseline to flame out. Patterns were created using the same window sizes (see Table 3) as the

training set. Prediction patterns created in this manner simulate the operation of the PNN in real-time as described below in step #5.

3. Feature selection was then performed either within *MAGICAL* (for *expert* and *calibsel*) or using a stand-alone MATLAB function (*varselpr*) for *FSPNNCV*. As discussed earlier, the features (variables) are the sensor magnitudes and slopes. Feature selection is useful for determining which sensors are critical for fire detection at a given alarm time and the importance of slope information at a given alarm time.

4. *MAGICAL* is used to perform PNN training using the variables chosen in step #3. PNNCV is used to estimate the prediction classification performance.

5. Using the trained PNN from step #4 and the prediction set from step #2, the MATLAB script, "*do_fire_pred*" is run. This routine implements PNN prediction for all patterns taken from each entire experiment. In the eventual application of this technology, the PNN will not operate on selected patterns (e.g., PNNCV), but will be fed pattern vectors continuously and asked whether that pattern can be classified as a fire event. Thus, playing back each experiment and creating pattern vectors as the fire and nuisance events evolve simulates the real-world application and is a realistic validation of the multi-criteria fire detection process.

6. The output results are formatted for easy interpretation using "*do_fire_data*", which is also written in MATLAB.

PNN Fire Classification Results

The results from the first series of experiments are shown in Table 4. These initial experiments focused on training the PNN at the alarm times for the three commercial photoelectric detector fire settings (sensor response times 1, 2 and 3). In this Table, the columns correspond to the experiment name, sensor response time method (1, 2 or 3), window size choice (A, B or C), the variables used for PNN training, the criteria for choosing the variables for PNN training (*expert, calibsel or FSPNNCV*), the percentage of patterns correctly identified in PNNCV analysis and the percentage of patterns experiments correctly identified in prediction using the "do_fire_pred" routine, respectively. The PNNCV training results are based on the 240 patterns used for training (82 fire, 38 nuisance and 120 baseline). For "do_fire_pred", the criteria for labeling a classification as successful are stringent but more realistic for real-time event monitoring. Success is credited for the 82 fire events when the PNN correctly identifies the event as a fire (i.e., "alarms") at *any* point after ignition. If the PNN alarms during the baseline period for *any* of the 120 experiments then the event is considered not correctly identified. Due to the short baseline periods for the majority of the experiments, window size choice C (option 8 in the MATLAB m-file), which computes the slopes from a 25 point window, often extends past the ignition time of the experiment. Thus, few "true" baseline periods are incorporated into the prediction performance for this window selection choice. Success is credited for the 38 nuisance events only when the PNN does not alarm at any point during the experiment. The *FSPNNCV* experiments were run multiple times with different sensors removed. Experiments starting with "25" were run with sensors 15, 16, 17 and 18 removed (RH, MICX, MICY and MICZ). The MIC

sensors (16, 17 and 18) were not included in the sensor combinations in experiments with names starting with "26". All sensors were included in experiments with names starting with "27".

Table 4. PNN Results using Sensor Response Times 1, 2 and 3

Name	Resp Time	Win. Size Choice	Sensors Selected	Sensor Select. Method	Train % (PNNCV)	Pred %
var1al1	1	A	16 21 22 7 4 12 5	Expert	95.00	80.83
var1al2	2	A	16 21 22 7 4 12 5	Expert	95.00	79.17
var1al3	3	A	16 21 22 7 4 12 5	Expert	94.17	77.50
var2al1	1	A	20 21 22 4 12 5 7	Expert	94.17	80.00
var2al2	2	A	20 21 22 4 12 5 7	Expert	94.58	78.33
var2al3	3	A	20 21 22 4 12 5 7	Expert	94.17	75.83
var3al1	1	A	20 21 22 4 7 12	Expert	93.75	79.17
var3al2	2	A	20 21 22 4 7 12	Expert	93.33	78.33
var3al3	3	A	20 21 22 4 7 12	Expert	92.50	75.83
var4al1	1	A	21 22 4 7 12	Expert	92.92	80.00
var4al2	2	A	21 22 4 7 12	Expert	94.17	78.33
var4al3	3	A	21 22 4 7 12	Expert	92.50	78.33
var5al1	1	A	16 21 22 20 18 17 7 4	Calibsel	94.17	80.83
var5al2	2	A	22 16 21 7 20	Calibsel	92.08	75.83
var5al3	3	A	22 16 21 7	Calibsel	89.17	75.83
var6al1	1	A	16 21 22 20 18 17 7 4	Calibsel	94.17	80.83
var6al2	2	A	22 16 21 7 20	Calibsel	92.08	75.83
var6al3	3	A	22 16 21 7 20	Calibsel	88.75	75.00
var7al1	1	A	16 21 22 20 18 17 7 4	Calibsel	94.17	80.83
var7al2	2	A	22 16 21 7 20 18 17	Calibsel	94.17	78.33
var7al3	3	A	22 16 21 7 20 3 18 17	Calibsel	92.92	78.33
var8al1	1	A	16 21 22 20 18 17 7 4	Calibsel	94.17	80.83
var8al2	2	A	22 16 21 7 20 18 17	Calibsel	94.17	78.33
var8al3	3	A	22 16 21 7 20 3 18 17	Calibsel	92.92	78.33
var9al1	1	B	16 21 22 20 18 17 7 24	Calibsel	95.00	80.83
var9al2	2	B	22 16 21 44 42 26 7 20 34 24 38 29 27 43	Calibsel	92.92	75.83
var9al3	3	B	22 16 43 21 44 38 7 24 26 29 42 27 34	Calibsel	93.33	76.67
var10al1	1	B	16 21 22 20 18 17 7 24 4	Calibsel	94.17	80.83
varl10al2	2	B	22 16 21 44 42 26 7 20 34 24 38 29 27 43	Calibsel	92.92	75.83
var10al3	3	B	22 16 43 21 44 38 7 24 26 29 42 27 34 40 25 39 33	Calibsel	90.00	73.33
var11al1	1	B	16 21 22 20 18 17 7 24 4	Calibsel	94.17	80.83
var11al2	2	B	22 16 21 44 42 26 7 20 34 24 38 29 27 43 40 18 17 39	Calibsel	93.75	76.67
var11al3	3	B	22 16 43 21 44 38 7 24 26 29 42 27 34 40 25 39 33 3 20	Calibsel	92.50	75.00
var12al1	1	B	16 21 22 20 18 17 7 24 4	Calibsel	94.17	80.83

Name	Resp Time	Win. Size Choice	Sensors Selected	Sensor Select. Method	Train % (PNNCV)	Pred %
var12al2	2	B	22 16 21 44 42 26 7 20 34 24 38 29 27 43 40 18 17 39	Calibsel	93.75	76.67
var12al3	3	B	22 16 43 21 44 38 7 24 26 29 42 27 34 40 25 39 33 3 20	Calibsel	92.50	75.00
var13al1	1	B	4 7 21 22 26 29 43 44	Expert	91.25	75.00
var13al2	2	B	4 7 21 22 26 29 43 44	Expert	88.75	74.17
var13al3	3	B	4 7 21 22 26 29 43 44	Expert	90.42	75.00
var14al1	1	B	3 4 7 21 22 25 26 29 43 44	Expert	92.50	77.50
var14al2	2	B	3 4 7 21 22 25 26 29 43 44	Expert	92.08	74.17
var14al3	3	B	3 4 7 21 22 25 26 29 43 44	Expert	93.33	74.17
var15al1	1	C	16 21 22 20 18 24 17 44 7	Calibsel	95.42	84.17
var15al2	2	C	44 22 16 21 34 26 27 43 7 24	Calibsel	94.17	76.67
var15al3	3	C	44 22 16 34 26 27 21 7 43 29 24 33	Calibsel	94.17	78.33
var16al1	1	C	16 21 22 20 18 24 17 44 7 4	Calibsel	96.25	83.33
var16al2	2	C	44 22 16 21 34 26 27 43 7 24 20	Calibsel	94.17	76.67
var16al3	3	C	44 22 16 34 26 27 21 7 43 29 24 33	Calibsel	94.17	78.33
var17al1	1	C	16 21 22 20 18 24 17 44 7 4 43	Calibsel	95.00	81.67
var17al2	2	C	44 22 16 21 34 26 27 43 7 24 20 29	Calibsel	94.17	76.67
var17al3	3	C	44 22 16 34 26 27 21 7 43 29 24 33	Calibsel	94.17	78.33
var18al1	1	C	16 21 22 20 18 24 17 44 7 4 43 26	Calibsel	95.00	80.00
var18al2	2	C	44 22 16 21 34 26 27 43 7 24 20 29	Calibsel	94.17	76.67
var18al3	3	C	44 22 16 34 26 27 21 7 43 29 24 33	Calibsel	94.17	78.33
var19al1	1	C	4 7 21 22 26 29 43 44	Expert	89.58	75.00
var19al2	2	C	4 7 21 22 26 29 43 44	Expert	92.92	75.00
var19al3	3	C	4 7 21 22 26 29 43 44	Expert	89.58	75.00
var20al1	1	C	3 4 7 21 22 25 26 29 43 44	Expert	92.92	77.50
var20al2	2	C	3 4 7 21 22 25 26 29 43 44	Expert	94.17	75.00
var20al3	3	C	3 4 7 21 22 25 26 29 43 44	Expert	90.83	75.00
25_1_1	1	A	5 11 21 6 10	Fspnncv	94.17	82.50
25_1_4	1	B	5 3 21 43 6 44	Fspnncv	95.42	79.17
25_1_8	1	C	5 3 21 10 8	Fspnncv	94.17	79.17
25_2_1	2	A	5 3 22 6 21	Fspnncv	96.25	78.33
25_2_4	2	B	5 22 3 6 19	Fspnncv	92.50	80.00
25_2_8	2	C	5 22 3 6 44 4	Fspnncv	93.33	78.33
25_3_1	3	A	5 14 22 13 7	Fspnncv	92.92	76.67
26_1_1	1	A	5 11 21 15 10	Fspnncv	95.00	85.00
26_1_4	1	B	5 3 15 21 22	Fspnncv	96.67	83.33
26_1_8	1	C	5 3 15 21 22	Fspnncv	96.67	83.33
26_2_1	2	A	5 3 22 15 4	Fspnncv	95.83	81.67
26_2_4	2	B	5 22 3 15 4	Fspnncv	93.33	82.50

Name	Resp Time	Win. Size Choice	Sensors Selected	Sensor Select. Method	Train % (PNNCV)	Pred %
26_2_8	2	C	5 22 3 15 4	Fspnncv	93.33	82.50
26_3_1	3	A	5 15 22 3 7	Fspnncv	93.75	79.17
26_3_4	3	B	5 15 22 3 43	Fspnncv	93.75	74.17
26_3_8	3	C	5 15 22 3 24 44	Fspnncv	92.50	79.17
27_1_1	1	A	5 11 21 5 10	Fspnncv	95.00	85.00
27_1_4	1	B	5 3 15 21 17	Fspnncv	96.67	89.17
27_1_8	1	C	5 3 15 21 17	Fspnncv	96.67	89.17
27_2_1	2	A	5 3 22 17 7 18	Fspnncv	97.92	81.67
27_2_4	2	B	5 3 22 17 7 18	Fspnncv	95.00	81.67
27_2_8	2	C	5 22 3 17 26 16	Fspnncv	95.83	79.20
27_3_1	3	A	5 15 22 3 7	Fspnncv	93.75	79.17
27_3_4	3	B	5 15 22 3 43	Fspnncv	93.75	74.17
27_3_8	3	C	5 15 22 3 18 27	Fspnncv	94.17	81.70

Several interesting observations can be made from the results in Table 4. It is very clear that *FSPNNCV* finds much better combinations of variables for PNN prediction than either *expert* or *calibsel*. This result is not surprising however since the SSE from PNNCV is used as the criterion for choosing the variables. While this may appear to bias the sensor selection process, the prediction results validate the procedure since "do_fire_pred" uses sensor readings (to create pattern vectors) from times that were not used in the variable selection process. In general there is a strong correlation between good PNNCV results and good prediction performance.

The best results found in Table 4 for response times 1, 2 and 3 were experiments 27_1_4 (variables 5, 3, 15, 21 and 17, [CO_{4000}, O_2, RH, SION and MICY]), 26_2_4 (variables 5, 22, 3, 15, and 4, [CO_{4000}, PHOT, O_2, RH and CO_{50}]), and 27_3_8 (5, 15, 22, 3, 18 and 27, [CO_{4000}, RH, PHOT, O_2, MICZ and ΔCO_{4000}]), which had prediction performances of 89.17%, 82.5%, and 81.7%, respectively. However, if you take the position that the MIC sensor (variables 16-18 and 38-40) is not practical for shipboard use then only the results from experiments starting with "25" and "26" can be used. Based on this criterion, experiments 26_3_8 (variables 5, 15, 22, 3, 24 and 44, [CO_{4000}, RH, PHOT, O_2, ΔCO_2 and ΔPHOT]) and 26_1_1 (variables 5, 11, 21, 15 and 10, [CO_{4000}, NO_2, SION, RH and NO]) were the best for sensor response times 1 and 3. There is a small drop-off in performance (89.17% to 85% at sensor response time #1 and 81.7% to 79.17% at sensor response time #3) caused by removing the MIC sensors from the array. Another decrease in prediction performance for the best sensor combination is found if the humidity sensor (#15) is dropped from the array (var2al1 = 80%, 25_2_4 = 80% and var4al3 = 78.33%, for sensor response times 1, 2 and 3, respectively).

All of the results listed for the *FSPNNCV* sensor selection method were based on the assumption of a 5-sensor array. To determine whether increasing the number of sensors would have a large payoff in detection accuracy or nuisance rejection a small subset of addition experiments were performed. Variable selection was performed to select the best subset of 5 through 8 sensors for experiment 26_3_8, which was the best performing combination at the earliest alarm time (response time #3) when MIC was not included. The results from these experiments are given in Table 5.

Table 5. Results from Varying the Number of Variables Used for PNN

Name	Resp Time	Win. Size Choice	Sensors Selected	Sensor Select. Method	Training % (PNNCV)	Pred %
26_3_8	3	C	5 15 22 3 24 44	Fspnncv	92.50	79.17
26_3_8b	3	C	5 15 22 3 24 44 20	Fspnncv	93.75	79.17
26_3_8c	3	C	5 15 22 3 24 44 20 33	Fspnncv	94.58	78.33
26_3_8d	3	C	5 15 22 3 24 44 20 33 29	Fspnncv	95.83	78.33
26_3_8e	3	C	5 15 22 3 24 44 20 33 29 11	Fspnncv	96.67	79.17

This small subset of experiments suggests that, at least at the earliest alarm times (PNN training times), adding more sensors will not dramatically improve the prediction results. In these experiments the slopes and magnitudes of PHOT and NO_2 were both chosen, so even though the PNN was trained on 10 variables, only 8 different sensors were chosen. The PNNCV results did systematically improve (92.5% to 96.7%), but the same trend was not seen in prediction. Thus, all further experiments will be based upon a 5-sensor array.

The results in Table 4 suggest that even earlier times could be used for fire detection because the fire detection accuracy did not significantly degrade at the 0.82% alarm time (response time #3). This provides further motivation for studying the sensor response time approach based on finding multiple sensors that had significantly different sensor readings versus their baseline response. The computational effort required to repeat the experiments in Table 4 with two other response times is extremely large. Thus, several decisions were made to downselect the number of experiments to a manageable level. Because *FSPNNCV* performed so much better than the other variable selection methods it was used for all experiments. Also because slopes were found to be useful at the earliest response times, it was decided that either window method B or C was necessary. If slopes were not found to be important *FSPNNCV* would always default to choosing variables that were not slopes (i.e., window selection #A). Although window selection methods B and C performed equally well, window selection method C was chosen for these experiments because it was found to be slightly better for PNN prediction at the earliest response times when MIC was not included (e.g., 26_3_8). It should be noted that according to the alarm times listed in Table 2, response times 4 and 5 are most similar to the 0.82% alarm level on the PHOT detector and thus window selection method C would appear to be the most suitable for these experiments. One additional experiment was performed to compare 5 and 6 sensor arrays for response time #5. Table 6 lists the results from the third series of experiments.

Table 6. PNN Classification Results from Response Times 4 and 5

Name	Resp. Time	Win. Size Choice	Sensors Selected	Sensor Select. Method	Train % (PNNCV)	Pred.%
Var30	4	C	3 5 15 26 27 34 O_2, CO_{4000}, RH, ΔCO_{50}, ΔEthy	Fspnncv	93.75	82.50
Var31	5	C	3 5 8 15 26 O_2, CO_{4000}, H_2S, RH, ΔCO_{50}	Fspnncv	95.83	87.50
Var31B	5	C	3 5 8 15 26 21 O_2, CO_{4000}, H_2S, RH, ΔCO_{50}, SION	Fspnncv	95.83	85.00

The results shown in Table 6 are better than those found in Table 4 when you consider that the alarm times are earlier than or equal to the 0.82% PHOT alarm level for most experiments. Recall from the discussion of Table 2 that the alarm time for response time #4 is 89 seconds (median value) faster than the alarm times at the 0.82% sensitivity level. As expected, for response time #4 slopes are very important. At this point during a fire or nuisance event, the sensor readings have not leveled off and the rate of change is critical. The slopes are slightly less important at response time #5 since only the slope of the CO sensor (variable 26) was chosen using *FSPNNCV*. It is also surprising that for these alarm times the importance of the smoke detectors is diminished. The RION smoke detector (variable 21) is only the sixth sensor selected at response time #5 and actually *degrades* the overall prediction performance slightly (87.5 to 85%), which is surprising. One of the consequences of this can be found upon further inspection of the misclassified events. When a smoke detector (either 21 or 22) is not included in PNN training an alarm is triggered during the baseline for experiment DCAS027.

Another interesting observation can be found upon further inspection of the outputs of the PNN plotted as a function of time. An example plot from 26_3_8 can be found in Figure 1. In this plot, the predicted probability of being a fire (0 = no fire, 1 = 100% certainty of being a fire) as determined by the PNN for DCAS028 (JP-5 fire) is plotted as a function of time. Overlaid on the probabilities are vertical lines which represent the ignition time (t = 100 seconds), alarm time of the PHOT sensor at the 11% commercial setting (t = 298 seconds) and the fire out time (t = 705 seconds), respectively. The PNN was organized such that if the predicted probability was greater than 0.5 (i.e., 50%) then an alarm is triggered. This decision threshold is indicated on the figure by the horizontal dotted black line. In this example, the PNN does a very good job at early warning fire detection, which is not surprising since it was trained on patterns taken from the 0.82% alarm time reading (sensor response method #3). However, prior to flame out the PNN output probability drops below the 0.5 cutoff level indicating that no fire is present. Because the PNN has not been trained to recognize fires and nuisance sources under those conditions the PNN fails to work correctly. Thus, to operate in real-world conditions the PNN may need to be trained using patterns taken from more than one point in the fire (e.g., baseline, early, middle and recovery). Although this is not the primary focus of these experiments, it might be beneficial to the other aspects of the DC-ARM program.

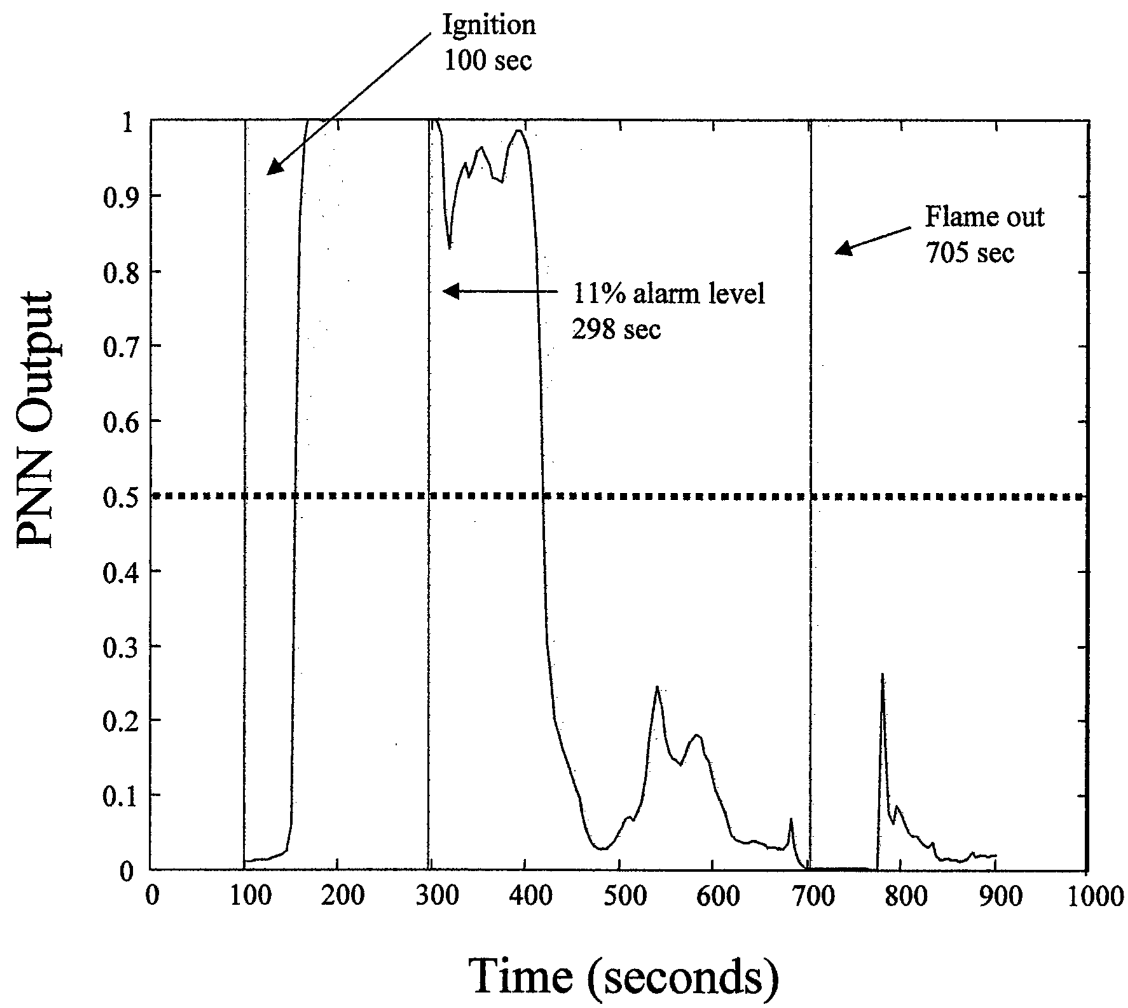

Figure 1. Plot of the PNN output (predicted probability of being a fire) as a function of time for DCAS028 (JP-5 fire). The red, magenta and green vertical lines represent the times for source initiation, 11% alarm level for PHOT and the flame out. The horizontal dashed line is the decision threshold for the PNN, which was set to 0.5 (50% probability). In this experiment, fire detection is accomplished quickly (within a minute of source initiation) but the fire is incorrectly classified (PNN output < 0.5) as a nuisance later in the event.

Using the training sets that have already been constructed experiments were performed using a PNN trained from multiple time periods. A PNN trained in this manner may be more suitable for a universal multi-criteria fire detection method than a PNN trained at a single point in time. Three PNN training sets (C45, C14 and C15) were constructed by combining the training sets for sensor response times 1, 4 and 5. PNN combination training set C45 consisted of patterns taken from sensor response times #4 and #5. Patterns taken from response times #1 and #4 were using to create PNN combination training set C14, while PNN combination training set C15 contained patterns using sensor response times #1 and #5. The PNN cross-validation and prediction results from the three combined training sets are shown in Table 7.

Table 7. PNN Classification Results from Combined Training Sets

Name	Resp. Time	Win. Size Choice	Sensors Selected	Sensor Select. Method	Train % (PNNCV)	Pred %
C45	4+5	C	5 3 15 34 8 CO_{4000}, O_2, RH, ΔEthy, H_2S	Fspnncv	92.50	88.33
C14	1+4	C	5 3 34 15 8 CO_{4000}, O_2, ΔEthy, RH, H_2S	Fspnncv	90.28	85.83
C15	1+5	C	5 3 15 21 8 CO_{4000}, O_2, RH, SION, H_2S	Fspnncv	95.00	90.83

The prediction results shown in Table 7 are a marked improvement over the results from a PNN trained using just one time period. The PNNCV results are similar to those found in Tables 4 and 6. However, the most noticeable difference can be found in the PNN output as a function of time. Figure 2 is a plot of the same experiment as Figure 1 (DCAS028). Using the PNN outputs from combination training set C15, it is clear that the PNN correctly identifies the fire during the majority of the experiment and recognizes when the fire has been extinguished and the room is clearing out.

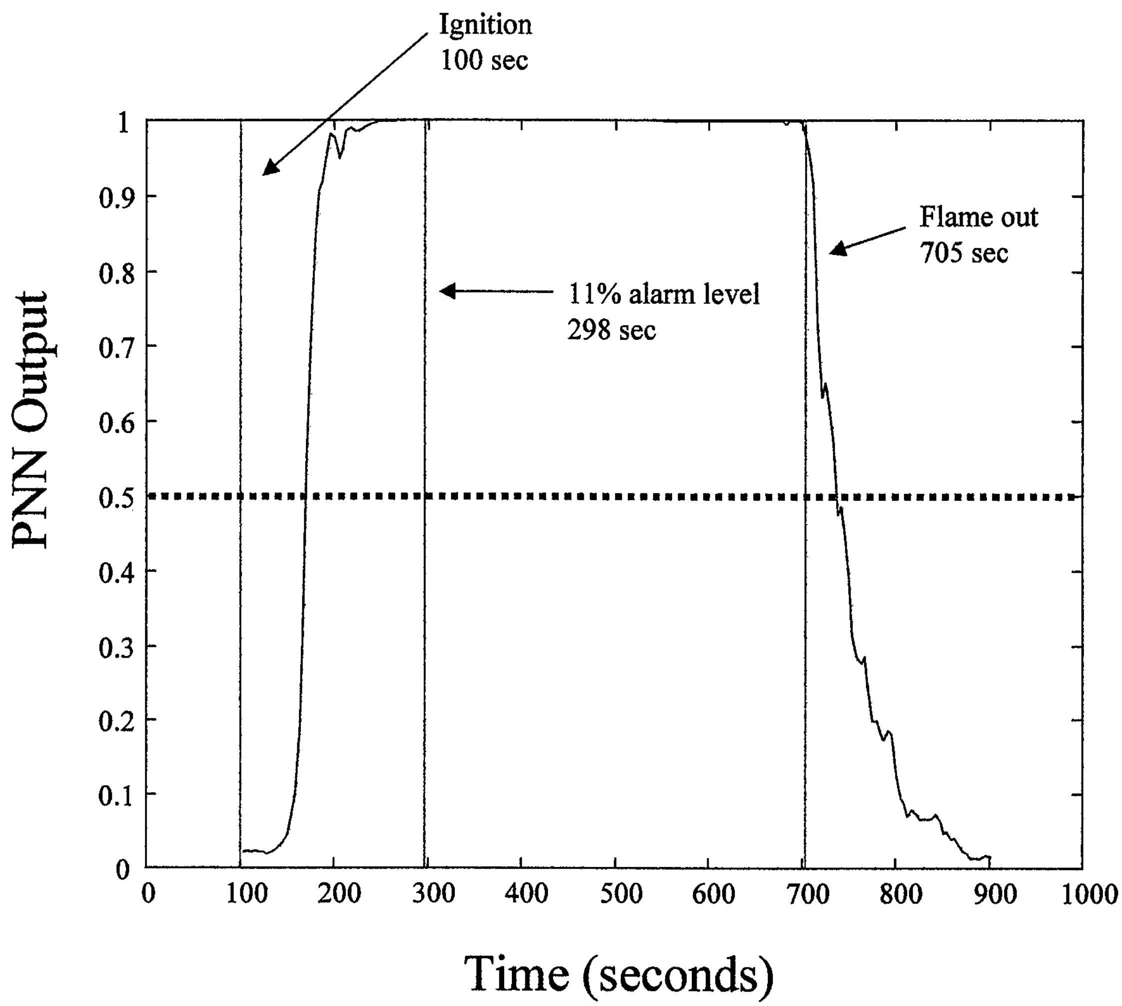

Figure 2. Plot of the PNN output as a function of time for DCAS028 (JP-5 fire). This plot is similar to Figure 1 but shows the output from a PNN trained under different conditions. The red, magenta and green vertical lines represent the times for source initiation, 11% alarm level for PHOT and the flame out. The horizontal dashed line is the decision threshold for the PNN, which was set to 0.5 (50% probability). In this experiment, fire detection is accomplished quickly, but unlike the plot shown in Figure 1 the event is correctly classified as a fire for the duration of the event.

Comparison with a Commercial Detection System and Previous Reports

In order to accurately assess the proposed NRL multi-criteria fire detection sensor array, it is necessary to place these results in context with the sensor arrays proposed in other NRL reports as well as the standard commercial systems. Our previous efforts in this area made the assumption that a "baseline" sensor reading could be found for the smoke and particle detectors so that a %obscuration per meter value could be determined [1,2]. The baseline would be used to calibrate the sensors at periodic intervals. In this work, we made the assumption that no baseline reading could be made and used the PNN directly on the raw values read from the smoke and particle sensors (MIC, PHOT, ION, SION and ODM). In both this work and our previous reports the gas sensors had been calibrated such that the PNN operated on engineering units (e.g., parts-per-million). The datasets used in references 1 and 2 also had been processed using a Savitsky-Golay filter, which does not lend itself to real-time operation, and the PNN was organized as a three-class problem (fire, nuisance, or background) rather than the two-class problem (real-fire or non-fire) described here. Thus, the datasets used in this work differ slightly from those used previously.

Table 8 lists the PNNCV results for a commercial detection system (PHOT, sensor #22), the best results from a previous report by Rose-Pehrsson and co-workers [1] (NRL #1), the best results from this work (NRL #2), and finally (NRL #3) a combination derived from using the sensors from NRL #1 on the datasets used in NRL #2. The first column in this Table represents the sensitivity level or response method used to generate the training set. The previous reports discuss the results in terms of sensitivity levels rather than sensor response times and so that terminology is used in the Table when referring to the previous results (note: 11%, 1.63% and 0.82% sensitivity levels are the same as sensor response time #1, #2 and #3 respectively). Overall detection accuracy is given in the third column. This value is computed the same as was done previously [1] based on 120 baseline patterns, 82 real fire patterns and 38 nuisance source patterns. When a combined training set is used (e.g., C15), the overall results are based on 120 baseline patterns, 82 real fire patterns at one response time, 82 real fire patterns at the second response time, 38 nuisance source patterns from one response time, and 38 nuisance source patterns from the second response time, to give a total of 360 patterns.

Table 8. Comparison of Fire Detection Performance Between Best NRL Detection Algorithms and Commercial Fire Detection Systems Based On PNNCV

Sensitivity Level	Sensors	Overall	Fire Detection	Nuisance Rejection
Commercial Photoelectric Detector				
11%	22	191/252 (75.8%)	34/88 (38.6%)	31/38 (81.6%)
1.63%	22	208/252 (82.5%)	62/88 (70.4%)	20/38 (52.6%)
0.82%	22	210/252 (83.3%)	64/88 (72.7%)	20/38 (52.6%)
NRL #1				
11%	3 8 15 21 22	234/240 (97.5%)	78/82 (95.1%)	36/38 (94.7%)
1.63%	3 8 15 21 22	234/240 (97.5%)	78/82 (95.1%)	36/38 (94.7%)
0.82%	3 8 15 21 22	227/240 (94.6%)	74/82 (90.2%)	33/38 (86.8%)
NRL #2				
Resp. 1	5 3 15 21 22	232/240 (96.7%)	76/82 (92.7%)	36/38 (94.7%)
Resp. 5	3 5 8 15 26	230/240 (95.8%)[a]	76/82 (92.7%)	36/38 (94.7%)
Resp. 5 + 1	5 3 15 21 8	342/360 (95%)[b]	153/164 (93.3%)	70/76 (92.1%)
NRL #3				
Resp. 1	3 8 15 21 22	231/240 (96.3%)	75/82 (91.5%)	36/38 (94.7%)
Resp. 5	3 8 15 21 22	227/240 (94.6%)	74/82 (90.2%)	33/38 (86.8%)
Resp. 5 + 1	3 8 15 21 22	340/360 (95.6%)[b]	151/164 (92.1%)	74/76 (97.4%)

[a] two false alarms on baseline patterns (DCAS025 and DCAS099)
[b] one false alarm on a baseline pattern (DCAS025)

These results illustrate that the large improvement in performance of a multi-criteria fire detection system using a sensor array and a PNN compared to the standard commercial detection system. The detection accuracy for NRL #1 is only slight better than can be found for NRL #2. It is interesting that several of the sensors were common to both the NRL #1 array and the NRL #2 array. Because background calibrations were not performed for NRL #2 the importance of the smoke detectors is lessened slightly. Thus, many of the best sensor combinations did not need a smoke detector to discriminate between fire and nuisance sources, especially at the higher sensitivity levels. However, the results from NRL#2 also suggest that when a smoke detector is not included in the sensor array the chances of a false alarm on background conditions increases. With this in mind, NRL #3 provides an interesting compromise. This array uses the sensors from NRL #1 with the training sets used for NRL #2. The classification performance of NRL #3 is equivalent to NRL #2. This is somewhat surprising because sensor #5 (CO) was found to be the most important sensor during this investigation, but is not present in the sensor array. This further highlights the difficulty in choosing an optimal sensor array based purely on pattern recognition results because of the high cross-selectivity between the gas sensors.

Further illustration of the impact of the cross-sensitivities can be seen in Figures 3A-3E. These plots are maps of the linear correlation coefficient (r) at alarm time 11% (A), 1.63% (B), 0.82% (C), response time #4 (D) and response time #5 (E). One interesting observation that can be found in these maps are that the correlations between sensors changes dramatically during the course of an event and this impacts which sensors are selected by the variable selection algorithms. At the response time #1 (11% alarm level), sensors 5 and 8 (CO_{4000} and H_2S) are highly correlated with each

other (0.72) and thus NRL #2 does not employ sensor #8 (H_2S). However, at response time #5, these sensors are not correlated any longer (0.17) and NRL #2 requires both sensors for high classification accuracy. Even with the smoke detectors, the correlation changes during the course of an event. Sensors #21 and #22 (SION and PHOT) are not correlated early in the event (response times #4 and #5) but become more correlated later in the event (response time #1). While the correlation between sensors generally grows as the event prolongs (response time #1) in some cases the correlation actually decreases. For example, sensor #3 (O_2) is less correlated ($r = -0.51$) with sensor #7 (HCl) at response time #1 than it is at response time #5 ($r = -0.62$) or response time #4 ($r = -0.85$).

Table 9 lists the real-time prediction results for the standard commercial system (same as Table 8) and NRL #2. These prediction results are obtained by simulating real-time operation of the PNN (i.e., "do_fire_pred"). As discussed previously, the real-time prediction results are slightly worse than those based upon the PNNCV due to the transient nature of fires. Fire signature patterns for a single source can change drastically during the course of an event. Thus, a nuisance source signature can appear to look more like a fire event signature to the PNN, if it has not been trained to discriminate between fires and nuisance sources during that portion of the event. A successful detection is given for the real fire events when the PNN correctly identifies the event as a fire (i.e., "alarms") at *any* point after ignition. Correct nuisance source rejection is credited when the PNN does not alarm at any point during the experiment. False positive detections occurring during the baseline period are included in the overall percentage correct. It should be noted that very few background patterns were actually tested since the NRL #2 array used a slope computed from 25 points, which is longer than the background period for most of the experiments. Future data collection efforts will need to be performed with longer baselines and typical background/ambient conditions.

Table 9. Comparison of Fire Detection Prediction Performance Between Best NRL Detection Algorithms and Commercial Photoelectric Fire Detection Systems

Sensitivity Level	Fire Detection	Nuisance Rejection
Commercial Photoelectric Detector		
11%	34/88 (38.6%)	31/38 (81.6%)
1.63%	62/88 (70.4%)	20/38 (52.6%)
0.82%	64/88 (72.7%)	20/38 (52.6%)
NRL # 2		
Resp. 5	81/82 (98.8%)	25/38 (65.8 %)
Resp. 5 + 1	81/82 (98.8%)	28/38 (73.7%)
Resp. 1	80/82 (97.6%)	27/38 (71.1%)

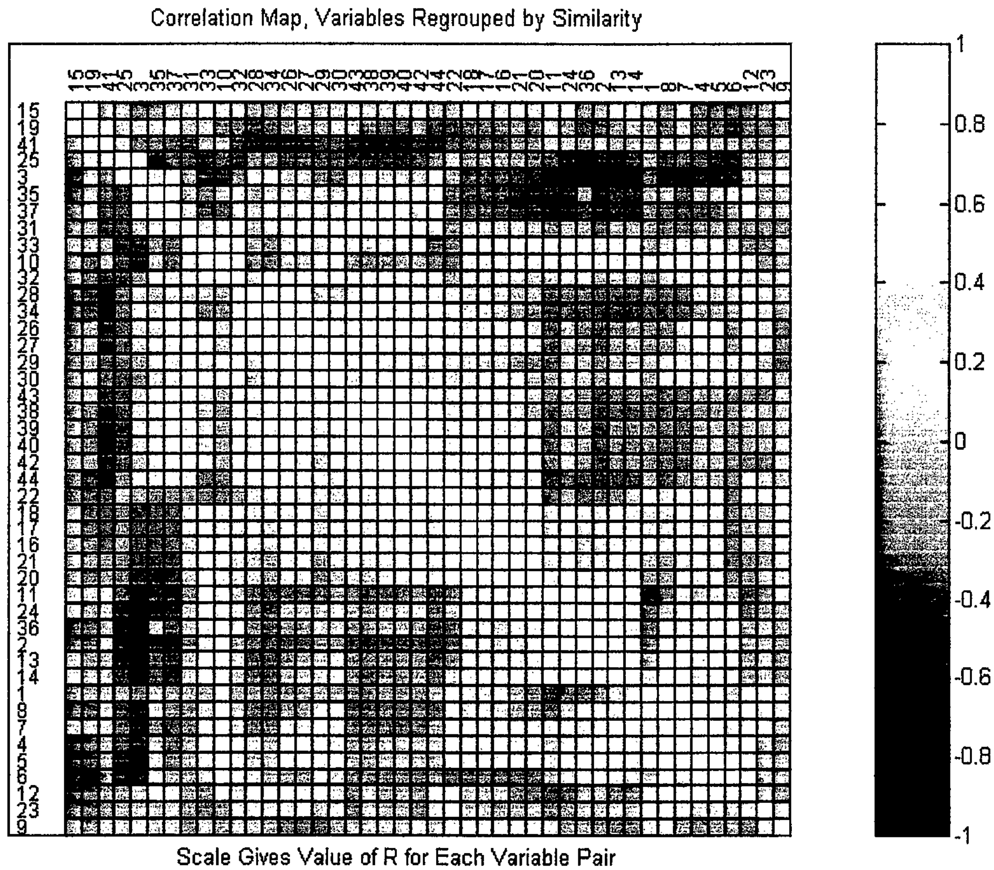

Figure 3A. Correlation map shows the linear correlation coefficient of the 22 sensor outputs from the PNN training set at response time #1 (11% obs./m). Highly correlated variables have coefficents near +1 or -1. Variables that are not correlated have values near 0.

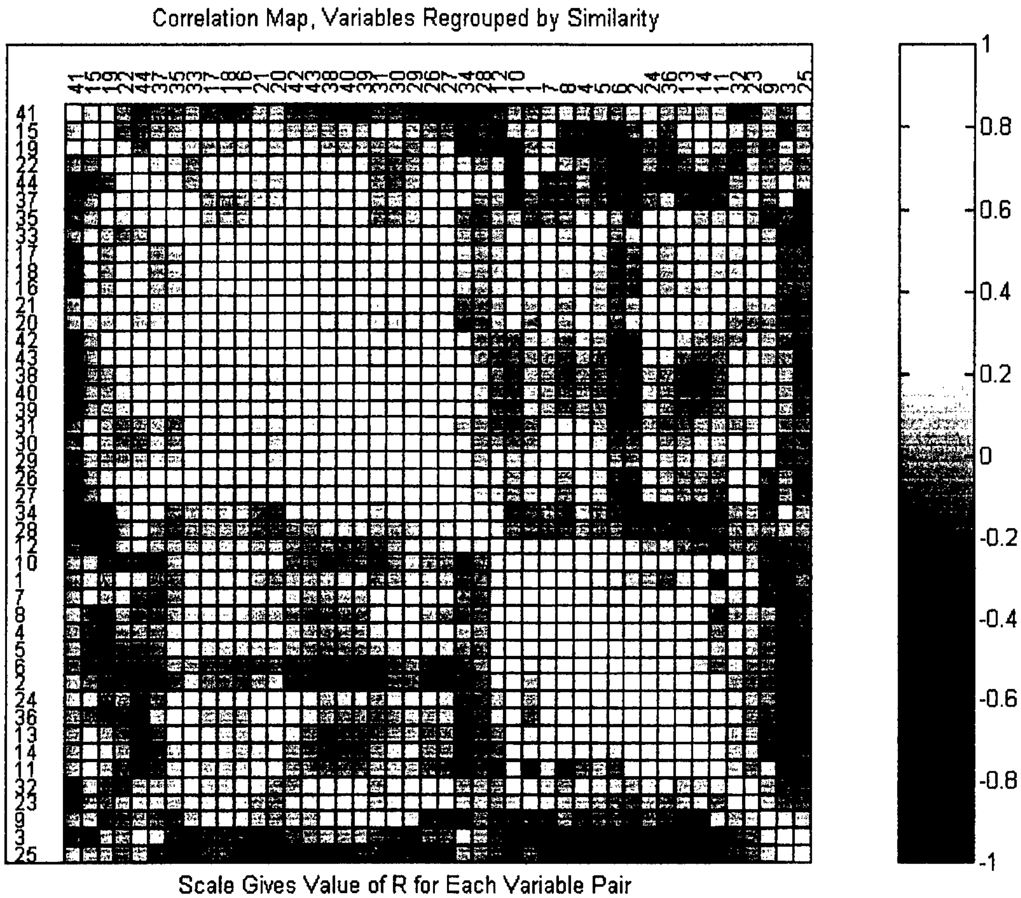

Figure 3B. Correlation map shows the linear correlation coefficient of the 22 sensor outputs from the PNN training set at response time #2 (1.63% obs./m). Highly correlated variables have coefficents near +1 or -1. Variables that are not correlated have values near 0.

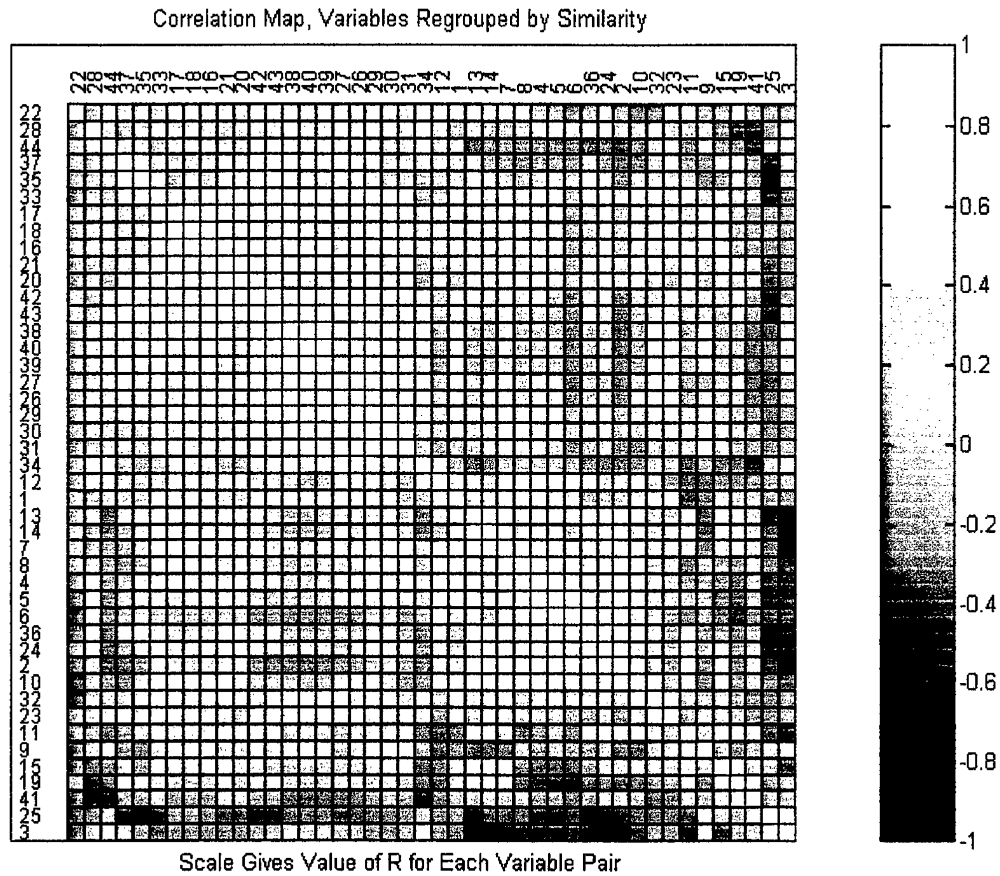

Figure 3C. Correlation map shows the linear correlation coefficient of the 22 sensor outputs from the PNN training set at response time #3 (0.82% obs./m). Highly correlated variables have coefficents near +1 or -1. Variables that are not correlated have values near 0.

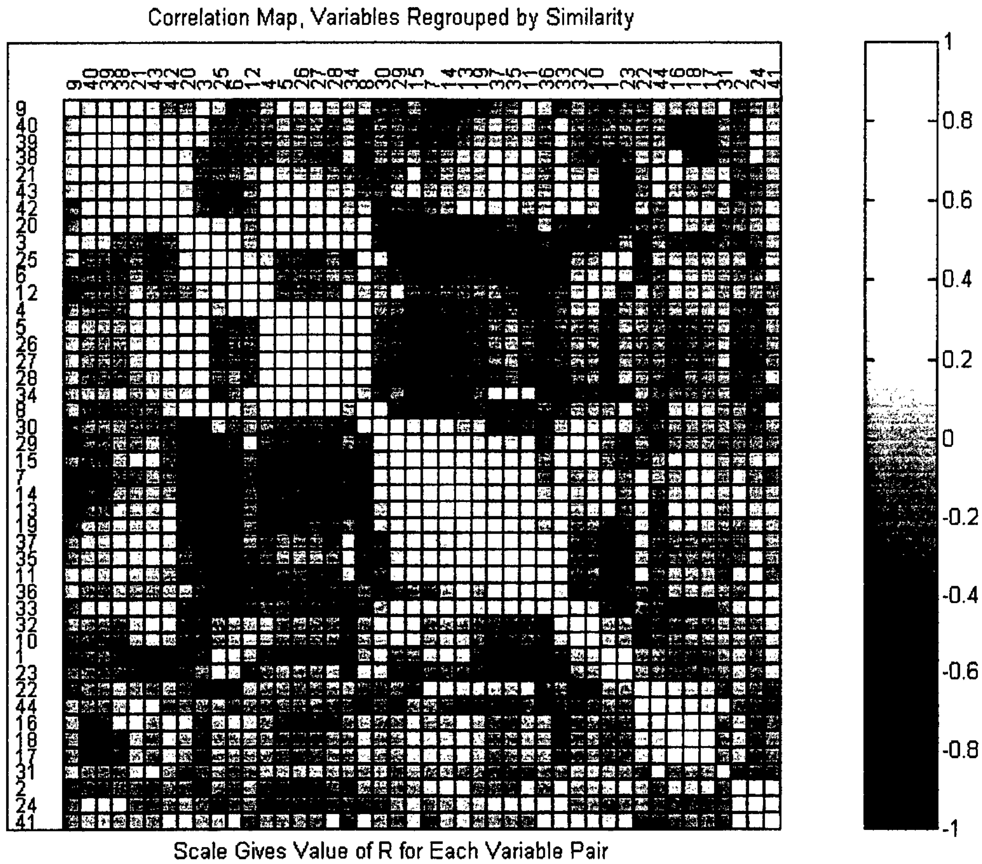

Figure 3D. Correlation map shows the linear correlation coefficient of the 22 sensor outputs from the PNN training set at response time #4. Highly correlated variables have coefficents near +1 or -1. Variables that are not correlated have values near 0.

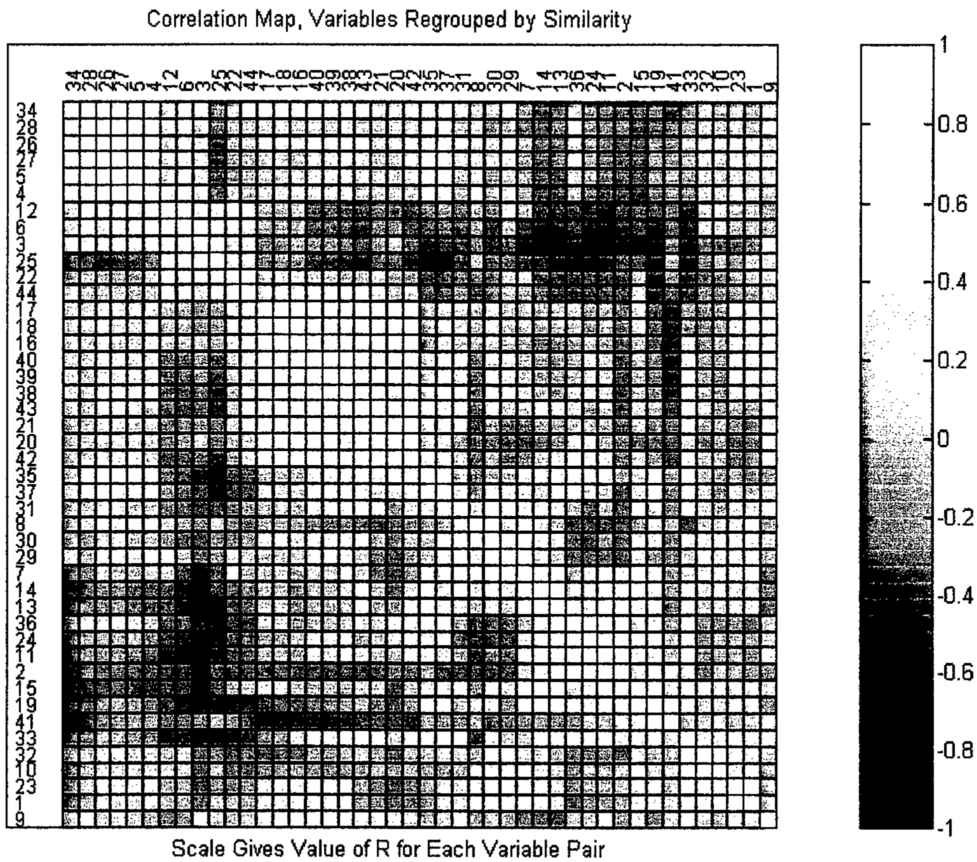

Figure 3E. Correlation map shows the linear correlation coefficient of the 22 sensor outputs from the PNN training set at response time #5. Highly correlated variables have coefficents near +1 or -1. Variables that are not correlated have values near 0.

Similar to Table 8 these results illustrate the excellent fire detection capabilities of the PNN based multi-criteria sensor array. This comparison is more realistic than comparing PNNCV results since the commercial detection systems were operating in real-time mode during the experiments. Further improvements must be made to increase the nuisance source rejection capabilities of the NRL sensor array. One simple modification that can be made is to increase the classification threshold, which is currently set at 0.5 (50%) as shown in Figures 1 and 2. In other PNN projects at the NRL the classification threshold has been successfully modified to meet the needs of the particular application [5,6]. This will be the subject of future experiments.

Conclusions

1. Earliest fire detection can be accomplished without a smoke detector but is prone to false alarms on background readings. False alarms occurring during the baseline time period, when the sensors are not purposely exposed to fire or nuisance materials, have a higher consequence than alarms found during a nuisance event (when the sensors are being challenged). Smoke detectors are an excellent source of information regarding when a fire or nuisance event (e.g., the sensors are being challenged or stimulated) is occurring because the smoke detector values change very little from day-to-day or experiment-to-experiment. They are less useful for discriminating between nuisance and real fire sources. Gas sensors provide the best information for discriminating between nuisance and fire sources, but are sometimes sensitive to changes in the background/ambient conditions of the room. Ultimately the best sensor suite will utilize both types of sensors. This report concludes that a combination of gas sensors and standard smoke detectors will provide for the best fire detection ability with the highest nuisance source rejection. A more difficult question is which gas sensors are needed. The PNNCV results point clearly to sensors #5 and #3 (CO and O_2), respectively as the best sensors for fire discrimination. Another sensor that was often found to be useful was the RH sensor (#15). One issue that may have affected the result is that the fire experiments were performed in a single fire chamber. It is not clear yet whether the conditions found at this site will be representative to the environments found in Naval ships. Future testing on board the ex-USS SHADWELL [7] will be required to address this issue. Other sensors that frequently turn up in the analyses as being important include sensors 2, 7, 8, 10, 11 and 12 (CO_2, HCl, H_2S, NO, NO_2 and hydrocarbons). Some sensors are better suited for early fire detection, while others tend to be better at the later points in time. It should also be noted that due to the cross-sensitivities (see Figures 3A-3E) of the electrochemical gas sensors, a single sensor may give information about many different gases at once, so it should not be surprising that a clear cut solution is not readily apparent. In terms of which smoke detector to use, sensors #21 and #22 (Simplex ionization and photoelectric) were found to provide the most useful information to the PNN. In some cases, the best 5 sensor combination included both, but in most cases the *FSPNNCV* selected one or the other.

2. This work showed that the sensor rate of change was only important early in the fire. At the 11% sensitivity level (response time #1) rate of change was never found to be important. In fact, only at the response times 3-5 did the rate of change regularly show up in the list of variables chosen by *FSPNNCV*. Even in those cases, the

magnitude reading was often more important than the rate of change. In several cases, it was found that computing the rate of change for a longer period of time (25 points = approx. 100-150 seconds) produced slightly better classification methods. Perhaps determining the rate of change over an even longer time period would also prove to be useful. It is expected that rate of change will be important for predicting data at other locations (e.g., ex USS Shadwell), because the inputs the PNN will be independent of ambient background gas levels. Issues such as "calibration transfer" or "sensor standardization" will be critical for the eventual application of this technology, since small changes in the inputs to the PNN may have undesirable effects, which may result in poor detection performance or nuisance source rejection.

3. The results shown in Tables 7 and 8 clearly point out that the best fire detection algorithm may need to include fire and nuisance patterns from multiple points in time or utilize multiple PNNs operating in parallel. For example, the PNN trained using alarm time #4 is geared toward detecting fires very early but is poor at discriminating between fire and nuisance sources that happen later in the event. This phenomenon is caused by the dynamic nature of fires, which causes the patterns for fires and nuisances sources to change during the course of an event. An interesting example of this can be found by interpreting the correlation maps in Figure 3. At the 11% alarm level, sensors 5 and 8 (CO_{4000} and H_2S) are highly correlated with each other and thus the FSPNNCV finds little use for sensor #8 (H_2S). However, at alarm level #5, these sensor readings are not correlated any longer and *FSPNNCV* finds both necessary for classification. Further studies will be required to elucidate the optimal method of applying the PNN so that it correctly identifies events early, which is most pertinent to the DC-ARM program.

4. An alternative approach to using the PNN for discrimination of fire, nuisance, and baseline patterns every time a new set of sensor readings are acquired would be to limit PNN classification decisions to cases when one of the smoke detectors reaches a certain criterion (e.g., 0.82% obs./m for PHOT). The ambient gas concentrations in a room are more apt to change quickly and thus trigger a false alarm from the PNN than a smoke detector such as PHOT or SION. A two-step approach, using one or more commercial smoke detectors as the filter or decision threshold, to reduce the number of PNN classification decisions has merit. A similar approach was used in previous NRL projects involving surface acoustic wave (SAW) sensor systems, which only used the PNN for cases in which a sensor frequency shift (compared to an established baseline) was greater than some preset threshold [5]. This two-step procedure greatly increased the robustness of the system and decreased the false alarm rate. During this work it was observed that the commercial fire systems rarely alarm during ambient background conditions. However, using the PNN with the sensor combinations studied here having both gas and smoke detectors in the array, several false alarms during background conditions were noted. Ultimately, a fire detection system with the fire detection capability of a commercial system at the 0.82% obs./m setting and the nuisance source rejection capability of a commercial system at 11% obs./m would be a significant advance. The results in this report have shown that the PNN has excellent nuisance source rejection capability at the 0.82% level with the data collected at the Hughes facility. A PNN trained at that alarm time would only have to be concerned with classifying a event as fire or nuisance since the chances of a true background having passed the criterion of 0.82% obs./m would seem unlikely. Furthermore, a nuisance event rarely reaches the 11% obs./m level on PHOT and many of those that do are often bordering on

being classified a fire at this point. Thus, the PNN might only need to operate (i.e., make classification decisions) when the smoke detector readings are between the 0.82% obs./m level and the 11% obs./m level. Anything above this level (for example) is automatically called a fire.

5. The results in Table 8 demonstrate that for a single environment it is not necessary to convert the smoke detector data to "engineering units" (i.e., Obs/m) in order to have high classification accuracy. Results found using NRL #2 and NRL #3 were comparable to those found in earlier work (NRL #1). One of the inherent limitations of this approach is that, if the final sensor array utilized a different smoke detector than was used during the PNN training phase, a correction factor will need to be determined to make the data from the new unit "look" like the data collected in the previously used unit. In order to provide accurate classification decisions, pattern recognition algorithms (e.g., PNN) require that the sensor data from the final unit have similar characteristics to the data collected during the training phase. In some cases a linear correction may be adequate to transfer the PNN model. Engineering units may also provide a common link for sensors from different manufacturers so that some flexibility is gained. Newly developed sensors could potentially be swapped for older ones without sacrificing detection accuracy or nuisance source rejection. The major disadvantage of converting the sensor data to engineering units is that an accurate baseline is needed. Further testing on board the USS-Shadwell will provide help in finding the optimal approach for this application.

6. It is the recommendation of this report that the optimal sensor combination will need to heavily consider practical issues such as sensor cost and maintainability in addition to pattern recognition performance. This work has shown that many different combinations of the sensors will lead to statistically equivalent discrimination performance. Without further experimental data from a shipboard site to use as an external prediction set, conclusions made in this report are also subject to bias from the experimental protocols used in the Hughes fire chamber tests. Thus, other factors will need to be considered along with the classification accuracy of the proposed sensor combinations to produce the best multi-criteria fire detection system.

References

1. Rose-Pehrsson, S.L., Shaffer, R.E., Hart, S.J., Williams, F.W., Gottuk, D.T., Strehlen, B.D, and Hill, S.A., "Multi-criteria Fire Detection Systems using a Probabilistic Neural Network, submitted to Sensors and Actuators, B.

2. Gottuk, D.T., Hill, S.A., Schemel, C.F., Strehlen, B.D., Rose-Pehrsson, S.L., Shaffer, R.E., Tatem, P.A., Williams, F.W., "Identification of Fire Signatures for Shipboard Multi-criteria Fire Detection Systems", NRL/MR/6180-999-8386, 6/18/99.

3. Shaffer, R.E., Rose-Pehrsson, S.L., and McGill, R.A., "A Comparison Study of Chemical Sensor Array Pattern Recognition Algorithms", Analytica Chemica Acta, 384, 305-317 (1999).

4. Shaffer, R.E., and Rose-Pehrsson, S.L., "Improved Probabilistic Neural Network for Chemical Sensor Array Pattern Recognition", Analytical Chemistry, 71, 4263-4271 (1999).

5. Shaffer, R.E., Cygan, M.T., Hart, S.J., Chung, R., Nguyen, V., Dilella, D., McGill, R.A., "Internal Standardization and Calibration of Surface Acoustic Wave Chemical Sensor Systems", Proceedings of the SPIE Conference on Electro-Optic, Integrated Optic, and Electronic Technologies for Online Chemical Process Monitoring, Volume 3537, pages 213-223 (1999).

6. Hart, S.J., Shaffer, R.E., Rose-Pehrsson, S.L., McDonald, J., "Using Physics-Based Modeler Outputs to Train Probabilistic Neural Networks for Unexploded Ordnance (UXO) Classification in Magnetometry Surveys", submitted to IEEE Transactions on Geoscience and Remote Sensing.

7. Williams, F.W., Toomey, T.A. and Carhart, H.W., "The ex-USS Shadwell Full-Scale Fire Research and Test Ship", NRL Memorandum Report 6074, 10/6/87, re-issued 9/92.